Evolutionary techniques for Sensor Networks Energy Optimization in Marine Environmental Monitoring

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ABSTRACT

The sustainable management of coastal and offshore ecosystems, such as for example coral reef environments, requires the collection of accurate data across various temporal and spatial scales. Accordingly, monitoring systems are seen as central tools for ecosystem-based environmental management, helping on one hand to accurately describe the water column and substrate biophysical properties, and on the other hand to correctly steer sustainability policies by providing timely and useful information to decision-makers. A robust and intelligent sensor network that can adjust and be adapted to different and changing environmental or management demands would revolutionize our capacity to wove accurately model, predict, and manage human impacts on our coastal, marine, and other similar environments. In this paper advanced evolutionary techniques are applied to optimize the design of an innovative energy harvesting device for marine applications. The authors implement an enhanced technique in order to exploit in the most effective way the uniqueness and peculiarities of two classical optimization approaches, Particle Swarm Optimization and Genetic Algorithms. Here, this hybrid procedure is applied to a power buoy designed for marine environmental monitoring applications in order to optimize the recovered energy from sea-wave, by selecting the optimal device configuration.

Keywords: Marine environment, Wireless Sensor Network, Optimization techniques, Computational Intelligence, Energy Harvesting Devices (EHDs)

1. INTRODUCTION

In the last few years the authors maturated experience in studying environmental measurement systems with particular attention to marine environment and relative policies for sustainable management. This kind of environment is particularly harsh and difficult or energy-efficient and sensitive measurement systems.

Wireless Sensor Network (WSN) are promising technology to enable different monitoring task compared to remote sensing techniques.[1–3] However, there are many significant impediments that presently restrict the adoption of WSNs in marine-based applications, especially in terms of available energy source for sensors. The recent advances in sensing and communication technologies contributed to increase the penetration of WSN in everyday life, in order to perform pervasive tasks even in completely new sector.[4] However the energy constraints of sensor networks, especially when their size increase, represent an additional aspect to be taken into account.

Linear generators are today increasingly used for energy conversion, since some energy sources, and especially marine ones, exhibit alternating motion. In fact, although renewable resources fed generators are usually characterized for presenting discontinuous phenomena with not very dense energy content, wave energy is one of the most promising renewable energy sources.[5] With respect to wind and photovoltaic, the energy associated to sea waves is more concentrated and consistent,[6] since it is related to the mechanical motion of a fluid significantly denser than air and it is caused by a phenomenon more intense than solar radiation even when a tracking system is used to increase overall PV-system performance.[7]

By starting on the research in the field of direct-drive linear machines,[8] this work aims to introduce a novel modeling design technique to optimize a tubular linear generator for sea wave energy conversion applications,[9]

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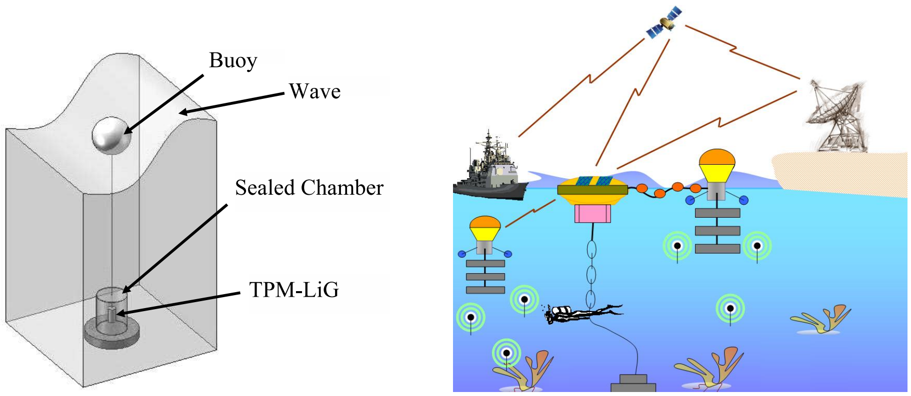


Figure 1. Simplified scheme of a power-buoy model with TMP-LiG and a potential marine scenario.

as illustrated in Figure 1. In this case the optimization is required in order to obtain voltage waveform close to the square wave to maximize the energy transfer.

In order to define an automated design process of the considered electromagnetic structure, a suitable optimization procedure must be considered. In this case, in fact, the use of a direct synthesis approach can be very difficult, since the complexity of the structure and the relevant number of parameters to be tuned in order to obtain the requested particular features.

In the SEMAT project[10] a specific research was performed to study low-cost sensor network system for monitoring aquatic and coastal ecosystems, and analyze the post-processed data to be used for management and planning purposes. This multidisplinary project aimed essentially at constructing smart sensor networks that can be deployed easily in aquatic settings.

This work can contribute to propose innovative self-sustaining power buoy to be integrated in wider networks for marine environmental monitoring applications, having the possibility to work disconnected from the main electric system similarly to the islanding concept in the smart grid context.[11]

2. WAVE ENERGY HARVESTING OPTIMIZATION

Traditional optimization approaches are, often, Newton-based methods or, in any case, related to gradient descent algorithms; these techniques, better known as local optimization algorithms, generally need to compute many derivatives in order to optimize the objective function. Given the large number of variables, and the possible presence of local optima, it is generally difficult to use these traditional optimization methods to find the global best solution of complex engineering problems.

To overcome these drawbacks, in recent years several numerical optimization techniques based on global search approaches, such as evolutionary algorithms, have been developed and widely applied to the design of electromagnetic devices.[12] Evolutionary algorithms in fact apply an indirect synthesis, by randomly choosing the parameters of interest and evolving their values towards an optimal solution; this means that one can control several parameters of the behavior of the structures to be designed, through a properly defined fitness function that puts constrains, *e.g.* on the resulting configuration and performances.

The new technique here proposed is based on two of the most known evolutionary optimization approaches: the Genetic Algorithm (GA)[13] and the Particle Swarm Optimization (PSO).[14] The description of the hybridization approach here proposed is briefly presented in this section.

Hybridization of optimization algorithms is getting popular due to their capabilities in effectively handling several engineering problems affected by complexity, noisy environment, imprecision, uncertainty and vagueness.[15]

Even though evolutionary computation has been widely accepted for solving several important practical applications in engineering and science, it is practically impossible to find the best algorithm for solving all

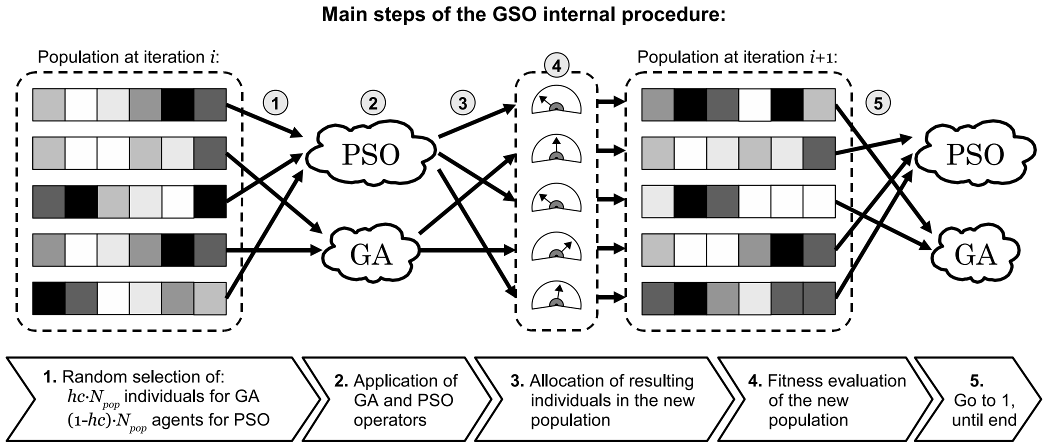


Figure 2. Flow chart of main operations performed by the GSO algorithm.

optimization problems. This is in accordance with the *No Free Lunch Theorem*,[16] which establish that for any algorithm, any elevated performance over one class of problems is offset by performance over another class.

As reported in literature,[15] several techniques and heuristics have been used to improve the general efficiency of the evolutionary algorithm. Some of most used hybrid architectures consist of a hybridization between an evolutionary algorithm and other evolutionary algorithms or similar computational intelligence techniques. The here proposed hybrid optimization algorithm has been created as an hybrid between GA and PSO.

In GA, the set of parameters that characterizes a specific problem is called an individual or a chromosome and it is composed of a list of genes. Each gene contains an encoding of a parameter to be tuned. Each individual therefore represents a point in the search space, and hence a possible solution to the problem. For each individual of the population a fitness function is therefore evaluated, resulting in a score assigned to the individual. GA simulate the natural evolution, in terms of survival of the fittest, adopting pseudo-biological operators such as selection, crossover and mutation to improve the fitness score associated to each individual.

In the PSO, the so called swarm intelligence (i.e. the experience accumulated during the evolution) is used to search the parameter space by controlling the trajectories of a set of K particles according to a swarm-like set of rules. In particular, the position X_k of the k-th particle represents a solution of the problem, and a fitness score is assigned to it.

Both the here considered algorithms are population-based iterative techniques with strong stochastic bases, consequently their performances are evaluated in terms of speed of convergence. In fact, the problem of premature convergence of the best individuals of the population to a local optimum is a well known drawback that can be found in these techniques. On the other hand, the use of these optimization techniques, requiring a relevant number of the cost function evaluations, needs particular care if, as in the present case, the cost function is computationally expensive.

To overcome these limits, a hybrid technique named Genetic Swarm Optimization (GSO) has been developed[17] and then applied for different applications.[18,19] Its basic concepts have been summarized in Fig. 2: in every iteration the population is randomly divided into two parts which are evolved with GA and PSO operators respectively. The fitness of the newly generated individuals is evaluated and they are recombined in the updated population which is again divided into two parts in the next iteration for the next run of genetic or particle swarm operators.

The driving parameter of GSO algorithm is the hybridization coefficient $hc(i)$, that indicates the percentage amount of population which is processed by genetic operators in each iteration i. The different rules of variation of $hc(i)$ during iterations identify several modes in the class of GSO algorithms, as shown in Ref. 17.

Therefore the authors proposed also two different adaptive rules, in order to combine in the most effective way the properties of the GA and the PSO approaches also for unknown problems.

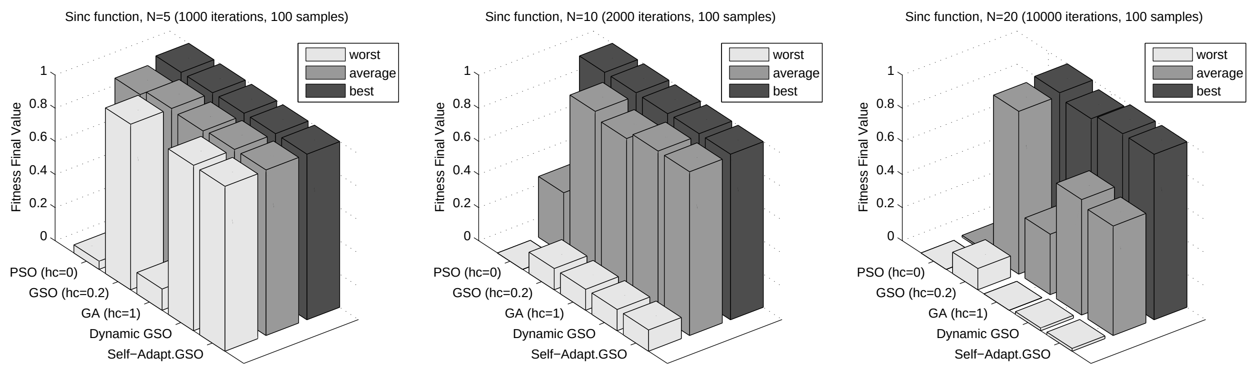


Figure 3. Final values of the *sinc* function optimization with $N = 5, 10, 20$ variables obtained with different hybridization strategies (average results over 100 trials)

Again in Ref. 17 several preliminary studies over different optimization tasks have been performed, showing a very high effectiveness of GSO in exploring the problem hyperspace, especially for the optimization of large domain objective functions.

In fact, as results reported in Figures 3 show, it seems that the improvements introduced by the hybridization are increasing with the dimension of the problem to be optimized. When $N = 10$ for example, the average performances of GSO are sligthy better than GA and significantly better than PSO (Figure 3), while, for $N = 20$, the improvement introduced by the hybridization is not negligible, since just the different GSO implementations are able to locate the optimal value, while, for the considered number of iterations, neither GA nor PSO are able to get the optimal value in 100 trials and their average performance is lower than GSOs' one. Moreover, the best performance is here obtained using $hc = 0.2$, since this value has been found to be the optimal for this kind of problem, but anyway the adaptive strategies are still better than the traditional techniques.

3. DEVICE OPTIMIZATION PROCESS

In this section the previous approach has been applied to the design of a tubular permanent magnet - linear generator (TPM-LIG) for sensorized buoy.[5,9]

A Tubular Permanent Magnet Linear Generator (TPM-LiG) is an electromechanical device able to convert linear motion in electrical energy when driven by a prime mover without any mechanical gearbox. This machine is equipped with a modular stator winding in which the coils of each phase are disposed adjacent to each other. In Ref. 20 an interesting study of the propagation of surge waves along the stator windings of induction machines is proposed. When the slider is moved the fluxes originated by PMs link each phase according to phases reciprocal distances so that an appropriate space shifting allows the desired output voltage generation. The parametric analysis presented in Ref. 21 also shows that is possible to modify the harmonics of the generated voltage in order to obtain a quasi-square or a triangular waveform as well. Such versatility is due to the physical complexity of the system, which depends on a large number of geometric and electromagnetic variables. This feature makes this technology suitable in renewables as marine energy harvesting, where TPM-LiG is commonly used in powerbuoys.

Supposing to employ this technology to supply a small electronic device as a wireless system, it is desirable to design the TPM-LiG so that the output voltage presents a constant value, since the available energy depends on the time-integral of power. Moreover, by using a three phase generator equipped with a simple AC-DC converter such as an ideal three-phase Graetz bridge, authors are interested to maximize the root mean square (rms) of rectified voltage, reducing as well as possible the ripple and the cogging force effects.

In respect of this objective a simulation tool based on FEM engine of "Finite Element Method Magnetics Software" has been built in Matlab environment as a numerical model connected to GSO algorithm. By means of an iterative computational cycle, the simulation tool measures the cogging force, the PMs fluxes in the stator armour behind each winding and it evaluates the electromotive force (EMF) assuming a continuous velocity as dynamic profile for the motion of slider.

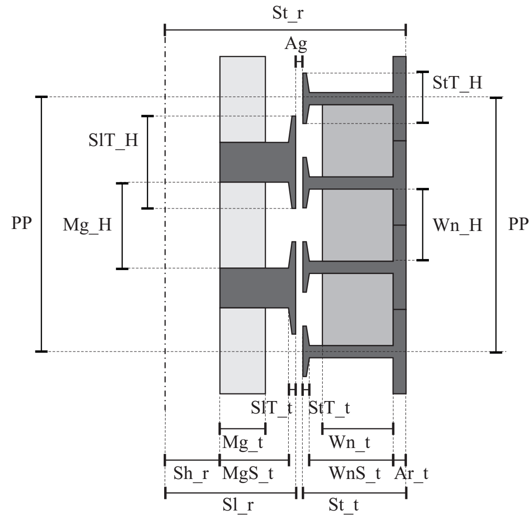


Figure 4. Schematic of TPM-LiG's geometric variables considered in the parametric analysis.

4. NUMERICAL MODEL AND TEST RESULTS

In power buoys the acting force is due to the Archimedes' law and it is proportionally to the volume of air constrained under the sea level by the buoy. When a wave passes over a buoy the sea level changes very rapidly determining a variation of the buoyant force in a very small period. For this reason, the peak values of applied force can raise up to 500 N with a small size buoy giving to the slider high velocity values. In this work authors have designed the generator to slide with a nominal 0.5 m/s peak square velocity.

The stator is equipped with three winding slots. The slot *fill factor* is assumed to be closed to 0.8, and the air gap in the winding slot is ignored in the simulation model. The slider consists of a hollowed shaft and permanent magnets separated by ironed spacers. A permanent magnet with grade $N42$ ($h_c = 955$ kA/m, $b_r = 1.32$ T), is used to provide a high density magnetic field. Magnets are axially magnetized and mounted alternately on the shaft. The core and the spacers are considered to be realized by using pure iron with nonlinear $B - H$ curve. The three coils cover a whole pole pitch to increase the linked flux and obtain a trapezoidal waveform. All the variables considered in the parametric analysis are shown in Figure 4 and the values selected by the optimization analysis are summerized in Table 1.

To analyze GSO performances first experiments over a magnetic test case were chosen as a benchmark optimization problem with a die press employed for the orientation of magnetic powder into anisotropic permanent magnet production. More details about definition of this problem can be found in Ref. 22.

In order to characterize the electromagnetic behavior of TPM-LiG a parametric analysis has been developed along the radial direction and along the axial direction, considering the effects of all the different parameters involved in the geometrical configuration of the machine at the same time. Authors have also defined two per-unit systems identifying a base unit quantity for each direction to maintain a general approach. As shown also in Table 1, this way allows to provide a dimensionless analysis since all the variables of the same axis are expressed as a fraction of a common defined base.

The data interface between optimization algorithm and numerical model is managed by a built-in function called *fitness function*. It is worth noting that the fitness function is the only link between the numerical model of the physical problem and the optimization procedure. The fitness function decodes the information provided by GSO into geometrical dimensions to assign to TPM-LiG design; afterwards, the fitness function analyzes the new configuration and then it evaluates the maximum peak value of cogging force (F_{cog}) acting on the slider, the the root mean square value (V_{rms}) and the per unit ripple value (V_{ripple}) of output voltage expressed as functions of slider position; the fitness function evaluates also the maximum value of EMF generated by moving PM's stored into the slider and the rms of rectified output voltage of AC-DC ideal converter.

Table 1. Geometrical Parameters Range

Variable	Name	Value [mm]
Axial Parameters		
Pole pitch	PP	21.00
Magnet height	Mg_H	$[0.60, 0.96] \cdot PP/2$
Slider tooth height	SlT_H	$[0.10, 0.80] \cdot PP/2$
Winding Height	Wn_H	$[0.30, 0.90] \cdot PP/3$
Stator tooth height	StT_H	$[0.20, 0.80] \cdot PP/3$
Radial Parameters		
Stator outer radius	St_r	$[20, 40]$
Air gap	Ag	1
Stator Thickness	St_T	$[0.30, 0.70] \cdot (St\_r - Ag/2)$
Winding thickness	Wn_t	$[0.70, 0.90] \cdot St\_t$
Stator armour thickness	Ar_t	$[0.05, 0.10] \cdot St\_r$
Shaft outer radius	Sh_r	$[0.40, 0.80] \cdot Sl\_r$
Magnet Thickness	Mg_t	$[0.70, 0.95] \cdot Sl\_r$

The selection of the parameters evaluated by the fitness function is crucial for the definition of the objective function. In fact, the aim of optimization algorithms is to find a solution that represents a global maximum or minimum in a suitably defined domain. In order to maximize the energy transferred by TPM-LiG from the sea-wave to the electronic load, it is desirable to have the greatest value of generated voltage with the rms value of rectified voltage close to one, which requires an EMF with a trapezoidal waveform. Moreover, it is necessary to reduce the cogging force as much as possible.

To reach out these different objectives, authors chose a constrained multi-objective approach by adopting thresholds for the fitness score value f in order to identify three different phases into the fitness score evaluation. Fitness score value f is then maximized by GSO according to the following expressions:

$$f = \frac{F_{1\,max}}{f_1}, \quad \text{if} \quad f_1 = \frac{V_{max} - V_{min}}{V_{max}} > F_{1\,max} \tag{1}$$

where f_1 is the per-unit ripple value of output voltage and $F_{1\,max}$ is the desired level for f_1. Whenever the ripple value f_1 stays above the threshold $F_{1\,max}$, the objective of GSO is to minimize it, as expressed by eq. (1);

When the value of f_1 is maintained below $F_{1\,max}$, the objective of GSO becomes:

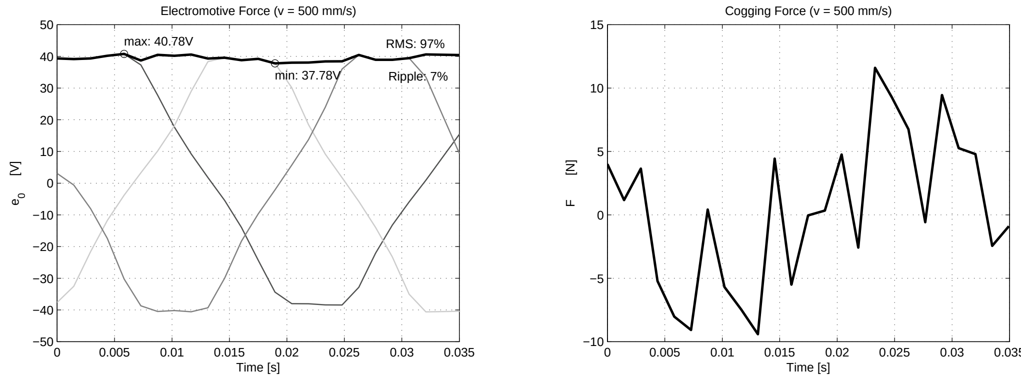
$$f = 1 + \frac{F_{2\,max}}{f_2}, \quad \text{if} \quad f_2 = \max(F_{cog}) > F_{2\,max} \tag{2}$$

This condition allows to minimize the maximum peak value of cogging force F_{cog}, until the second threshold $F_{2\,max}$ is reached. In fact, $F_{2\,max}$ represents the desired maximum level of F_{cog}.

When the value of f_2 is maintained below $F_{2\,max}$, in order to maximize the rms of output voltage V_{out} the objective function f becomes:

$$f = 2 + \frac{f_3}{F_{3\,min}} \tag{3}$$

where $f_3 = \min(V_{out})$ represents the minimum desired level for the rms output voltage V_{out}.



(a) (b)

Figure 5. Time-dependent Electromotive Force (a) and Cogging Force (b) values (slider velocity = 500 mm/s).

The objective function described above is defined to achieve three subsequently objectives: produce an high, quasi-constant output voltage with the smallest cogging force. Any fitness score value $f > 3$ means that all the requirements have been satisfied. Figure 5(a) shows how it is possible to achieve a trapezoidal shape of EMF in order to take advantage of a quasi-constant rectified voltage. It is worth noting that the optimized configuration provides an rms value of EMF equal to 70.85% of its maximum value per phase with respect to 70.62% presented by a sinusoidal waveform. Neglecting the losses due to the Graetz bridge, the rms value of rectified voltage is equal to about 97% of maximum output voltage V_{out}, with a ripple of about 7%. As shown in Figure 5(b), the cogging force effects are reduced into the interval $[-20, 20]$ N causing an oscillation less than 5% on the average applied force of 500 N.

5. CONCLUSIONS

In this paper a novel hybrid optimization technique has been presented and then applied to the optimization of electromagnetic devices. In particular the method has been effectively used for the optimization of a tubular linear generator for sea wave energy conversion. Here the optimization procedure was applied to a marine device for environmental monitoring in order to optimize the energy recovery and device endurance. This kind of device can be potentially integrated in wireless sensor network architectures for marine applications. The automated soft-computing technique here presented was effectively used to optimize the electromagnetic behaviour of the TPM-LiG device which seems to represent a promising well-suited technology for power generation in several marine applications such as power buoys.

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